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Design and Implementing Brain tumor Detection Using Machine Learning Approach

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ABSTRACT

In this paper, we propose a brain tumor segmentation and classification method for multi-modality magnetic resonance image scans. The data from multi-modal brain tumor segmentation challenge are utilized which are co-registered and skull stripped, and the histogram matching is performed with a reference volume of high contrast. We are detecting tumor by using preprocessing , segmentation, feature extraction ,optimization and lastly classification after that preprocessed images use to classify the tissue .We performing a leave-oneout cross-validation and achieved 88 Dice overlap for the complete tumor region, 75 for the core tumor region and 95 for enhancing tumor region, which is higher than the Dice overlap reported.

I. INTRODUCTION

The detection and diagnosis of brain tumor from MRI is crucial to decrease the rate of casualties. Brain tumor is difficult to cure, because the brain has a very complex structure and the tissues are interconnected with each other in a complicated manner. Despite many existing approaches, robust and efficient segmentation of brain tumor is still an important and challenging task. Tumor segmentation and classification is a challenging task, because tumors vary in shape, appearance and location. It is hard to fully segment and classify brain tumor from mono-modality scans, because of its complicated structure. MRI provides the ability to capture multiple images known as multimodality images, which can provide the detailed structure of brain to efficiently classify the brain tumor. shows different MRI modalities of brain.

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The brain images taken as input and that images performs the preprocessing operation after the preprocessing segmentation using the k-means algorithm and on that segmented area we perform the operation feature extraction using the classification SVM and CNN algorithm.

This technique can be developed to classify the tumors based on feature extraction. the detection of brain tumor is fast and accurate

when compared to the manual detection carried out by clinical experts.

II. Methodology

- Support Vector Machine The objective of the support vector machine algorithm is to find a hyperplane in an N-dimensional space(N—the number of features) that distinctly classifies the data points.

- Possible hyperplanes To separate the two classes of data points, there are many possible hyperplanes that could be chosen. Our objective is to find a plane that has the maximum margin, i.e the maximum distance between data points of both classes. Maximizing the margin distance provides some reinforcement so that future data points can be classified with more confidence.

- Hyperplanes in 2D and 3D feature space Hyperplanes are decision boundaries that help classify the data points. Data points falling on either side of the hyperplane can be attributed to different classes. Also, the dimension of the hyperplane depends upon the number features. If the number of input features is 2, then the hyperplane is just a line. If the number of input features is 3, then the hyperplane becomes a two-dimensional plane. It becomes difficult to imagine when the number of features exceeds 3.

- Support Vectors Support vectors are data points that are closer to the hyperplane and influence the position and orientation of the hyperplane. Using these support vectors, we maximize the margin of the classifier. Deleting the support vectors will change the position of the hyperplane. These are the points that help us build our SVM.

- Large Margin Intuition In logistic regression, we take the output of the linear function and squash the value within the range of [0,1] using the sigmoid function. If the squashed value is greater than a threshold value(0.5) we assign it a label 1, else we assign it a label 0. In SVM, we take the output of the linear function and if that output is greater than 1, we identify it with one class and if the output is -1, we identify is with another class. Since the threshold values are changed to 1 and -1 in SVM, we obtain this reinforcement range of values([-1,1]) which acts as margin.

- CNN (Convolutional Neural Network)

- Mathematical Working and Flow of CNN:

[1] Input Layer — has input size [7, 1] because we have 7 features
[2] conv1d— First convolutional layer
[3] averagePooling1d — First average pooling layer
[4] conv1d — Second convolutional layer
[5] averagePooling1d — Second pooling layer
[6] flatten — Reduce the dimension, reshape input to [number of samples, number of features]
[7] dense — Fully connected layer using linear activation function with 1 unit which returns 1 output value

- Convolutional neural network (CNN) is part of the family of neural network (NN) which is a variation of a multilayer perceptron (MLP). CNN consists of an input layer, several hidden layers and an output layer like any other NNs. Input layer is a representation of identity function, f(x) = x. Output layer which makes decisions, passes previously calculated weights through a linear function. Hidden layers are either convolutional, pooling, dropout or fully connected. In addition, all layers have activation functions at the end which gives additional functionality

  e.g. normalization. sigmoid , tanh and RELU are examples of these activation functions. Weights of convolution layers can be seen as 2D- filters and they apply convolution operation with these filters. Convolution operation is a process which sums the point-wise multiplications of given two functions while sliding the operation window. Pooling layer generalizes the elements in window frame while sliding this window. For example, max pooling outputs the maximum elements for a given window while sliding it. Dropout selects several neurons, that feed the input of next layers and reduces overfitting. Finally, fully connected layers can be thought as a fully connected version of classical MLP. With the explanation of fully connected layers, CNNs can be seen as a combination of MLP and filters which can operate as either convolution or pooling. In order to optimize weights of CNN, we have used an adaptive learning rate method (ADADELTA) optimizer. Apart from the fact that CNNs give noteworthy performance , they require much more data compared to other types of models. With the purpose of solving this issue, we merge all ETFs and create a satisfactory dataset for a financerelated problem. Additionally, merging reveals that we do not have to stick to one set of stock only. The model trained with this dataset, assumed that it performs well, will be universal for all kinds of stocks rather than a particular stock.

tanh(x) = 1 e2x/ 1 + e2x (1)
(x) = 1 1 + ex (2)
R(x) = max(0, x) (3)

yi = 01 + 1xi1 + ... + pxip = xT i , i = 1, ..., n (4)
where T denotes the transpose and xT i is the inner product between two vector.

A. Project outline

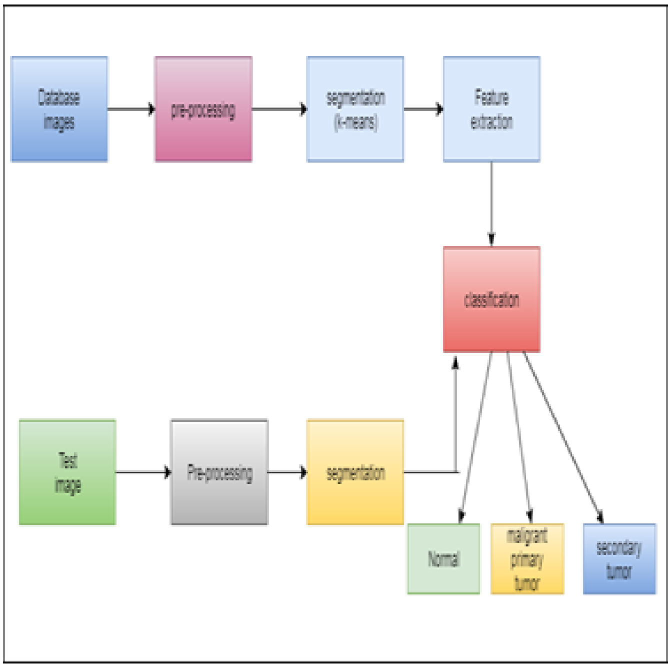

Figure 1: Overall Architecture

B. Brain image Preprocessing

Due to existing noise disturbance the MR images get affected. For noise reduction the research work proposes local smoothing methods and nonlocal means. In the image there may also exist few significant structures and details that can act as noise; such kind of details are also eliminated. The technique of Image pre-processing involves: data cleaning, data transformation, data integration, data resizing, data reduction etc. The image pre-processing eliminates unnecessary data and smooth up noisy data, detect and eliminate the outlier and rectify the data inconsistencies. Lastly, normalization and aggregation is performed. The technique of Image-processing proves to be highly significant in determining particular heart image, removing noise and for improvising the quality of the image

C. Average filtering

The normal channel being the convolution work that is utilized to set the clamor in the images. The Pre-processing step abandons the disturbances in the image but still after applying preprocessing the image doesn't hold suitable for future process. As a result the Average channel resolves this issue by

providing acceptable and smooth picture. The Average channel resembles a non-linear channel unlike straight channels. The Average channel replace the pixel esteems with an Average esteem that being nearly accessible (like, 3x3 or 5x5 or pixels near the focal pixel esteem). Moreover, Average channel tends to be edge safeguarding. It helps in abandoning salt and pepper disorder.

Algorithm:

Step 1 : The picture is provided as input.
Step 2 : Choose a 3X3 window near the current pixelwithin the picture.
Step 3 : Perform pixel sorting in expanding request andsave it to vector.
Step 4 : Determine the normal of the vector.
Step 5 : The current pixel is replaced with the normalesteem.
Step 6 : Repetition of means 2 to 5 till every single pixelswithin the picture gets prepared.
Step 7 : Output.

D. Pixel based segmentation

Image Segmentation is a common technique of digital image processing. Lately, Brain tumor image sectioning in MRI has spurred up as a popular research in the domain of medical imaging system. The process of Segmentation

E. Convolution Neural Networks

Convolutional Neural Network – CNN is employed for segmenting the images. It directly extracts features from pixel images with least pre-processing involved. The network utilized is LinkNet which being a light deep neural network architecture that's developed to carry out semantic segmentation. The LinkNet Network contains encoder and decoder blocks which basically manage to split the image and re-build again before it's forwarded via few final convolutional layers. CNN is a significant approach of deep learning which is being employed in image recognition applications. It involves two basic methods of

convolution and pooling. Convolution and pooling layers are arranged till high level of classification accuracy is achieved. Moreover, few feature maps are identified in every convolutional layer and weights linked to convolutional nodes (in the same map) are being shared. Such arrangements offer comprehension of various network characteristics at the same time retaining the no: of traceable parameters. CNN possess less specific tasks in contrast to the conventional methods and helps in thoroughly extracting features. Figure 2, depicts the CNN process scheme as.

Algorithm for CNN based Classification

Step 1 : Convolution filter is applied in the first layer.

Step 2 : The filter sensitivity is minimized by smoothingthe convolution filter that is by sub- sampling.

Step 3 : The activation layer controls the signal transferfrom one layer to other layer.

Step 4 : Training period is being fastened by employingRELU (rectified linear unit).

Step 5 : The neurons in proceeding layer is associated witheach neuron in the next layer.

Step 6 : At the time of training, Loss layer is appended inthe end to provide a feedback to NN (neural network).

F. Evolution metrics

For performance evaluation and measuring system stability, few parameters are computed and examined. These are mentioned as:

The proposed CNNs performance is assessed with RMSE(Root Mean Square Error), recall, sensitivity, precision, F-score specificity, PME (probability of the misclassification error) and accuracy of the training and testing set and throughout performance was examined by making use of the Eqs. (1-8) correspondingly, where Y_i

denotes actual and R_i denotes result of the i^{th} diagnosis of brain tumor feature acquired, TN (True Negative) denotes prediction for the patients with no brain tumor and were detected with no brain tumor, FN (False Negative) denotes the prediction for the patients with no brain tumor but were detected with a brain tumor, TP(True Positive) denotes the prediction for the patients with brain tumor and were detected with a brain tumor, and FP(False Positive) represents the prediction for the patients having brain tumor but were detected with no brain tumor.

- True Positive (TP): If the instance is positive and it is classified as positive
- False Negative (FN): If the instance is positive but it is classified as
- True Negative (TN): If the instance is negative and it is classified as negative
- False Positive (FP): If the instance is negative but it is classified as positive.

III. LITERATURE RIVIEW

S r n o	Title	Authors	Yea r	Description
1	Semi-Automatic Segmentation Software for Quantitative Clinical Brain Glioblastoma Evaluation	Ying Zhu, MS, Geoffrey S. Young, MD, Zhong Xue, PhD, Raymond Y. Huang, MD, PhD, Hui You	2011	Our software adopts the current state-of-the-art tumor segmentation algorithms and combines them into one clinically usable pipeline.
2	A novel content-based active contour model for brain tumor segmentation	Sachdeva J, Kumar V, Gupta I, Khandelwal N, Ahuja CK	2011	Brain tumor segmentation is a crucial step in surgical and treatment planning. Intensity-based active contour models such as gradient vector flow (GVF), magneto static active contour (MAC) and fluid vector flow (FVF) have been proposed to segment homogeneous objects/ tumors in medical images.
3	New developments in liposomal	B.S.	20	Five decades of research in the

	drug delivery	Pattni, V.V.	14	Field of liposome research have shown their prospective benefits in the
		Chupin and V.P. Torchilin		medical and cosmetic as well as the food industry.
4	Liposomal drug delivery systems: From concept to clinical applications	T.M.	20	The first closed bilayer phospholipid systems, called liposomes, were described in 1965 and soon were proposed as drug
		Allen and P.R. Torchilin	14	delivery systems.

IV. CONCLUSION

In this paper we are presenting an algorithm to hierarchically classify the tumor into three regions: whole tumor, core tumor and enhancing tumor. Intensity, intensity difference, neighborhood information and wavelet features will be extracted and utilized on multi-modality MRI scans with various classifiers. The use of SVM and CNN classifier will increase the classification accuracy as evident by quantitative results of our proposed method which are comparable or higher thanthe state of the art.

V. REFERENCES

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